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Nonlinear Processes in Geophysics

An artificial neural network predictor for tropospheric surface duct phenomena

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Abstract. In this work, an artificial neural network (ANN) model is developed and used to predict the presence of ducting phenomena for a specific time, taking into account ground values of atmospheric pressure, relative humidity and temperature. A feed forward backpropagation ANN is implemented, which is trained, validated and tested using atmospheric radiosonde data from the Helliniko airport, for the period from 1991 to 2004. The network's quality and generality is assessed using the Area Under the Receiver Operating Characteristics (ROC) Curves (AUC), which resulted to a mean value of about 0.86 to 0.90, depending on the observation time. In order to validate the ANN results and to evaluate any further improvement options of the proposed method, the problem was additionally treated using Least Squares Support Vector Machine (LS-SVM) classifiers, trained and tested with identical data sets for direct performance comparison with the ANN. Furthermore, time series prediction and the effect of surface wind to the presence of tropospheric ducts appearance are discussed. The results show that the ANN model presented here performs efficiently and gives successful tropospheric ducts predictions.

1 Introduction

The presence of tropospheric ducts leads to various effects on the radio-wave propagation, such as trapping, deep slow fading, strong signal enhancement and multipath fading. The knowledge of the presence of such phenomena is important in communications and radar systems, since it can lead to frequency, transmission angle and power adjustments in order to achieve optimum propagation and detection respectively. The characteristics of the evaporation duct channels, which are always present above the sea surface, can be predicted using various models, as for example the Babin-Young-Carton (BYC) (Babin et. all, 1997), the Paulus-Jesce (PJ) (Paulus, 1985) and Musson-Genon–Gauthier–Bruth (MGB) (Musson-Genon et al.,1992). In this work, pattern recognition algorithms, such as ANNs and SVMs are used in order to predict the presence or not of a tropospheric duct, using only the surface values of Pressure, Humidity and Temperature.

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According to the IEEE std 211-1997, refractivity is defined as the amount by which the real part of the refractive index, n, exceeds unity. According to the ITU-R Recommendation P.453-9 it is defined as:

$$N = (n-1)\cdot 10^6 = \frac{77.6p}{T} - \frac{5.6e}{T} + \frac{3.75\cdot 10^5 e}{T^2} \tag{1}$$

Where
N is the radio refractivity,
p is the atmospheric pressure (hPa),
e is the water vapour pressure (hPa) and
T is the absolute temperature (Kelvin degrees)
The above equation can be simplified and expressed as:

$$N = \frac{77.6}{T}\left(p + \frac{4810e}{T}\right) \tag{2}$$

If the relative humidity, RH, is given, the water vapour pressure can be found using the following set of equations (ITU-R P.453-9, 2003):

$$e = \frac{RH}{100} a e^{\left(\frac{bT}{T+c}\right)} \tag{3}$$

Where the temperature is given in °C and the coefficients a, b and c take the following values:

a) For Water (–20 to +50 °C): $a = 6.1121$, $b = 17.502$, $c = 240.97$

b) For ice (–50 to 0 °C): $a = 6.1115$, $b = 22.452$, $c = 272.55$

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Alternative forms of equations that relate the water vapour pressure to the relative humidity can be found in (Lear, 1980) and (Patterson et al., 1994).

The function of refractivity in respect to height, $N(h)$, can be expressed as:

$$N = N_0 e^{-\frac{h}{H_s}} \tag{4}$$

Where N_0 is the refractivity at the surface level,
h is the height and
H_s is the atmospheric scale height.

Equation (4) is valid under normal atmospheric conditions were pressure and temperature have an exponential relation to height. Temperature inversions or high evaporation rates above sea surfaces that occur in the lower atmosphere may cause the refractivity to deviate from the above formula, resulting in abnormal propagation conditions.

In order to define those refractive conditions in the troposphere, (e.g. subrefractive, superrefractive, ducting e.t.c.) the modified refractivity (or refractive modulus) is used:

$$M = (n - 1 + \frac{h}{R}) \cdot 10^6 = N(h) + 0.157h \tag{5}$$

Where h is the height and R is the Earth's radius. The gradient of the modified refractivity determines the refraction type, while tropospheric ducting phenomena occur when the following condition is met:

$$\frac{dM}{dh} < 0, or \frac{dN}{dh} < -157 \tag{6}$$

2 Data and Analysis

The data used for the current study were supplied by the Hellenic National Meteorological Service (HNMS) and are the temperature, the relative humidity and the altitude at constant pressure levels, measured at the Hellenico Airport of Athens Meteorological Station (37.9 N, 23.73 E) using radiosondes launched twice a day (00.00 and 12.00 LT). The data set covers the time period from January 1991 to December 2004 and the atmospheric pressure levels from ground atmospheric pressure down to 7 hPa.

In order to avoid possible unwanted influence or biasing, no data recovery or interpolation techniques were implemented for missing or out of range values, except for several humidity profiles where a simple linear interpolation was applied in order to fill in small gaps. In general, days including a large number of abnormal (excessively high deviations with altitude) or missing values were simply removed from the data set.

2.1 Artificial neural network implementation

For the prediction of the tropospheric ducting phenomena, a 3-13-1 feed forward backpropagation network was implemented, including the input layer, a linear output layer, and a tangential-sigmoid hidden layer (Table 1). Thus, a classifier is developed, which merely associates ground values of pressure, relative humidity and temperature and predicts the presence of a duct for the specific observation time. The selection of the tangential-sigmoid transfer function for the hidden layer allows any nonlinear relation between the system predictors and the output. A hard-limit transfer function for the output layer could also be used for the direct prediction of ducts presence through the hard-labels of the output. In this case, even if a direct result can be obtained, the models output cannot be adjusted according to a desired level of sensitivity and specificity threshold. The number of neurons used in the hidden layer was empirically chosen and corresponds to the value that maximizes the model's performance.

The network predictors consist of an 3xN matrix, where each row represents the ground pressure, relative humidity and temperature respectively for a total of N measurements per dataset, while each column stands for the days used. The target vector has a binary form, its elements being 1 in case of duct presence for the specific day and 0 in case of tropospheric duct absence. The presence of the ducts was determined by applying the whole data set to the equations of section 1and these values were used as training and test set outcomes. Since the available data correspond to midday (12.00 LT) and midnight (00.00 LT), different statistics for the presence of ducts are expected. Therefore, each data set is treated separately.

In order to determine the minimum required number of the training epochs and to avoid the overtraining of the network, at each run, two years (2001 and 2002) were used to validate the training process. Thus at each iteration the computed weights and biases provide a solution which is compared to the validation data. As soon as the error outputs show an increasing tendency, the training process stops and the values of the weights and biases that correspond to the epoch of the minimum validation error are obtained. Furthermore, data from two years (2003 and 2004) were used for testing, while the rest of the dataset (1991 to 2000) were used for training the ANN.

Since the required number of training years required to obtain satisfactory results is essential for the deployment of the system in a station where no long term radiosonde data are available, the model was simulated under an incremental training data set consisting of one to twelve years (1991, 1991 to 1992, 1991 to 1993 etc). In this case, the data from year 2003 were used for validation purposes, while year 2004 was used for testing.

In order to validate the ANN results and to investigate for any further improvement of the proposed method, the problem of tropospheric ducts prediction was treated using two Least Squares Support Vector Machine (LS-SVM) (Suykens & Vandewalle 1999) classifiers. They were trained using the two data batches from 00:00 LT and 12:00 LT measurements. The two models were trained using the same datasets so that the results are comparable.

Table 1. Artificial Neural Network Characteristics.

ANN Type:	Feed Forward Backpropagation
Training Procedure:	Batch Training using Levenberg-Marquardt optimization algorithm
Number of Layers:	1 input – 1 hidden – 1 output
Number of Neurons:	3-13-1
Transfer Functions:	Linear – Sigmoid Hyperbolic Tangent – Linear Symmetric Saturating

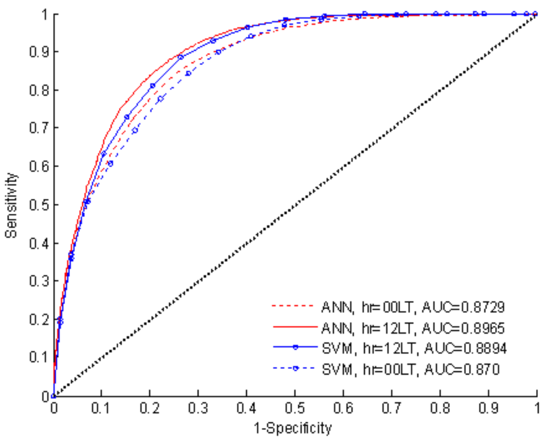

Fig. 1. ANN and SVM mean ROC curves (LT=00:00 and LT=12:00) and corresponding AUC values. Training: 1991–2000, Validation: 2001–2002, Testing: 2003–2004.

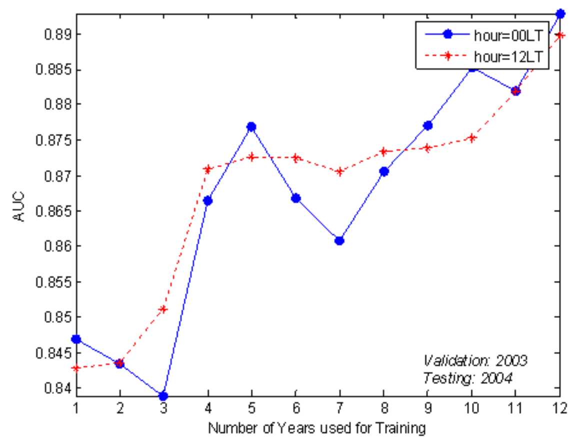

Fig. 2. The ANN performance (AUC) using variable training set from 1991 to 2002 and fixed validation (2003) and testing (2004) data (LT=00:00 and LT=12:00).

2.2 Support vector machines implementation

The second method utilized for the problem of tropospheric ducts prediction is Least-Squares Support Vector Machines (LS-SVMs). This supervised learning method is based on the underlying statistical learning theory of SVMs as developed by Vapnik in (Vapnik 1999). Support vector machines map input vectors to a higher dimensional space where a maximal separating hyperplane is constructed. Two parallel hyperplanes are constructed on each side of the hyperplane that separates the data and maximizes the 2 classes' distance. An assumption is made that the larger the margin or distance between these parallel hyperplanes the better the generalisation error of the classifier will be. This formulation can be used for both classification and regression problems. The key advantages of this approach include easy handling of very high dimensional datasets, strong statistical foundation, lack of suboptimal solutions (local minima) and sparseness of the resulting support vectors.

LS-SVMs (Suykens & Vandewalle 1999) are an addendum to the baseline SVM methodology that aims to simplify the solution process by reducing it to a linear rather that quadratic optimization problem. However this comes with the side-effect of loss of the sparseness of the solution. For additional information on SVMs and their variants the interested reader is refered to (Cristianini 2000, Burges 1998).

It must be noted that SVMs like ANNs and other generic pattern analysis algorithms are not aimed at describing the mechanism of the underlying phenomena, but rather to provide a reliable "black-box" method of predicting them, given a minimal collection of features and samples.

In the context of the current application we used duplet of classification LS-SVMs, each assigned to map the binary effect of duct presence on two series of time-points at hours 00:00 and 12:00. The kernel used was a Radial Basis Function (RBF). Training and testing processes were taken identical with the corresponding ANN models, as described above, to facilitate direct performance comparison. The SVMs were trained using a range of parameters $\gamma \in [0.1\ 1]$ and $\sigma \in [1\ 30]$. Using a Bayesian optimization procedure as in (Suykens & Vandewalle 1999) the final optimized parameter estimates were chosen to be γ=0.164 and σ=8.55. Where γ is the parameter that controls the trade off between problem regularization and data fitness and σ is a parameter specific to RBF kernel.

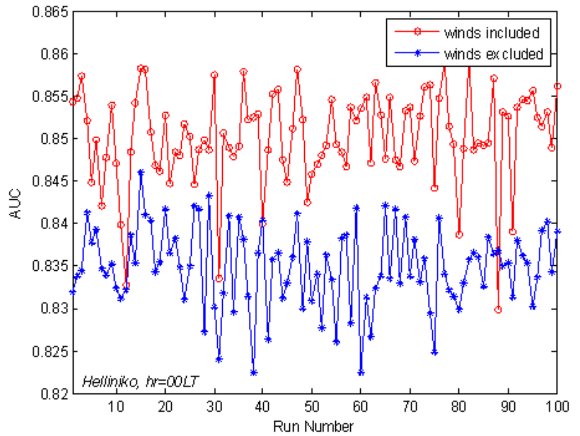

Fig. 3a. ANN AUC for various runs under random initial weights and biases, when winds were and were not taken into account (Helliniko, LT=00:00). Training: 1991–2000, Validation: 2001–2002, Testing: 2003–2004.

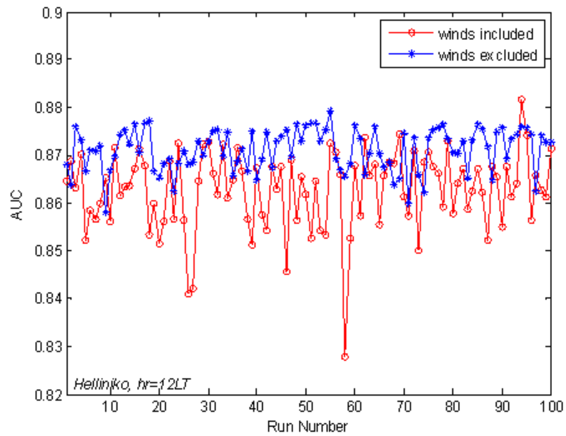

Fig. 3b. ANN AUC for various runs under random initial weights and biases, when winds were and were not taken into account (Helliniko, LT=12:00). Training: 1991–2000, Validation: 2001–2002, Testing: 2003–2004.

Table 2. ANN and SVM mean ROC curves Characteristics.

	AUC	95% CI (−)	95% CI (+)
	h=00:00 LT		
ANN	0.872	0.869	0.877
SVM	0.870	0.866	0.873
	h=12:00 LT		
ANN	0.896	0.893	0.899
SVM	0.889	0.885	0.893

3 Results and discussion

Both ANN and LS-SVM classifiers were trained and simulated for a significant number (100) of times each, using random initial values for the weights and biases. In this way, the model's generalization is assessed, while its dependence on the initial parameters settings is revealed. For each initialization, the metric used was the AUC (Fawcett, 2004), in order to decouple the performance estimate from the specific threshold chosen by the classifier. Confidence intervals were also calculated for each model, in order to define the model's prediction boundaries.

In Fig. 1, and Table 2 the mean ROC Curves and the corresponding 95% confidence intervals are shown, for 00:00 and 12:00 LT, for both models. In this diagram, which shows the efficacy and generality of the classification procedure, the x-axis stands for the specificity and describes the false alarm rate i.e. erroneous tropospheric duct prediction, while the y-axis stands for the sensitivity, which expresses the successful duct prediction rate. In both cases the curves tend to (x,y)=(0,1), while the 95% confidence intervals span is very small, showing that both models achieve a good level of generalization, while most probably the predictive capacity of the used features cannot be extended any further.

Figure 2 shows the AUC obtained for 00:00 and 12:00 LT, by training the ANN with variable number of years. Thus, at each training attempt the ANN model is given an increasing number of training years as input, while the validation and testing data sets remain the same and correspond to 2003 and 2004 respectively. This diagram expresses the number of years required to achieve a specific AUC value. It is obvious, that even if a single year is used for training, an AUC value greater than 0.84 is achieved, while increasing the number of years, the models' response (expressed here by the AUC values) is improved, as expected, due to the corresponding increment of the training data set values. This means that even if systematic radiosonde data collection does not exist, a season's measurements of Pressure, Temperature and Humidity with respect to height can lead to the development of a complete ducting prediction model.

To explore the possibility of time series prediction (regression) we attempted fitting a pair of similar LS-SVM and ANN models using as additional input variables, the measurements taken within a sliding window consisting of the current plus the previous two days measurements. Thus each dataset consisted of nine predictors. The results obtained were only marginally different from the simpler single-timeslot models. Consequently, the prediction is not augmented by temporal information, probably due to the large intervals between corresponding measurements (24 h). It has to be noted, that various feed forward time delay backpropagation networks were also tested using different time (day) delays, yet their results did not enhance the model's performance. We can therefore conclude that even if the ducting phenomena show seasonal variations and increase during the summer period (Isaakidis et. al., 2004) they are not correlated to consecutive days previous to the day analyzed.

In order to study the ground wind effects on tropospheric ducting appearance, the ANN and LS-SVM classifiers were fitted using the ground values of wind force and wind speed as additional variables, forming a 5xN predictors matrix. In Figs. 3a and 3b, the AUC values when the winds data were and were not included are shown, for the Helliniko Airport (00:00 LT and 12:00 LT). It can be seen that inclusion of wind values did not improve the AUC. This implies that in the way that the wind parameters were used in the model, as surface force and speed, they cannot be directly related to the appearance of ducting conditions. The effect of surface winds to the ducting phenomena should be further investigated.

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